Continued Development of the Look-up-table (LUT) Methodology for Interpretation of Remotely Sensed Ocean Color Data and Fusion of Hyperspectral Imagery with LIDAR Bathymetry

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Award Number: N0001404C0218
http://www.onr.navy.mil/sci_tech/32/322/ocean_optics_biology.asp

LONG-TERM GOAL

The overall goal of this work is to refine and validate a spectrum-matching and look-up-table (LUT) technique for rapidly inverting remotely sensed hyperspectral reflectances to extract environmental information such as water-column optical properties, bathymetry, and bottom classification. The work also seeks to combine hyperspectral imagery and LIDAR bathymetry to improve the capabilities of both.

OBJECTIVES

My colleagues and I are developing and evaluating a new technique for the extraction of environmental information including water-column inherent optical properties (IOPs) and shallow-water bathymetry and bottom classification from remotely-sensed hyperspectral ocean-color spectra. We address the need for rapid, automated interpretation of hyperspectral imagery. The research issues center on development and evaluation of spectrum-matching algorithms, including the generation of confidence metrics for the retrieved information.

APPROACH

The LUT methodology is based on a spectrum-matching and look-up-table approach in which the measured remote-sensing reflectance spectrum is compared with a large database of spectra corresponding to known water, bottom, and external environmental conditions. The water and bottom conditions of the water body where the spectrum was measured are then taken to be the same as the conditions corresponding to the database spectrum that most closely matches the measured spectrum.

In previous LUT work, we have been simultaneously retrieving water column IOPs, bottom depth, and bottom classification at each pixel from the remote-sensing reflectance R_{rs} spectra. This is much to ask from a simple R_{rs} spectrum, but we have conclusively shown that all of this information is uniquely contained in hyperspectral reflectance signatures and that the information can be extracted with considerable accuracy (Mobley et al., 2005). Nevertheless, in many situations of practical interest, additional information, such as LIDAR bathymetry or in-water measurements of inherent optical properties (IOPs, namely the absorption, scattering, and backscatter spectra), will be available and should be used to constrain the LUT retrieval for the remaining unknown quantities.

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE **30 SEP 2006**	2. REPORT TYPE	3. DATES COVERED **00-00-2006 to 00-00-2006**

4. TITLE AND SUBTITLE **Continued Development of the Look-up-table (LUT) Methodology for Interpretation of Remotely Sensed Ocean Color Data and Fusion of Hyperspectral Imagery with LIDAR Bathymetry**	5a. CONTRACT NUMBER 5b. GRANT NUMBER 5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER 5e. TASK NUMBER 5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Sequoia Scientific, Inc,2700 Richards Road, Suite 107,Bellevue,WA,98005**	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR'S ACRONYM(S) 11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited

13. SUPPLEMENTARY NOTES

14. ABSTRACT

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT **unclassified**	b. ABSTRACT **unclassified**	c. THIS PAGE **unclassified**	**Same as Report (SAR)**	**7**	

Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

There is currently much interest in combining LIDAR bathymetry with hyperspectral imagery. In such a situation, the LIDAR can be use to recover accurate bathymetry over part or all of the area seen by the hyperspectral imager. The LIDAR-retrieved bottom depths can then be taken as known when performing the LUT spectrum matching to obtain water column IOPs and bottom classification. Knowing the bottom depth (which in some situations also may be known from nautical charts or from acoustic surveys) removes one of the unknowns in the LUT spectrum matching, and we consequently expect that the LUT recovered IOPs and bottom classification will then be more accurate.

WORK COMPLETED

This year's work centered developing LUT R_{rs} inversion code that allows the depth to be either unknown or known at each image pixel. When the depth is known for a given pixel, only the bottom reflectance and water-column absorption, scatter, and backscatter spectra are retrieved by the LUT inversion. This is called a depth-constrained inversion. If no depth is available for a given pixel, then the bathymetry is also retrieved. This is an unconstrained inversion in which no assumptions are made about the environment being imaged. It is also possible to do IOP-constrained inversions, or depth- and IOP-constrained inversions, in which case only the bottom classification remains as an unknown. I used the new code in to investigate what improvements in LUT retrievals of bottom classification and IOPs can be achieved if the bathymetry is known from a LIDAR or acoustic survey of the imaged area. I also studied what improvements can be obtained in retrieved bathymetry and bottom classification if the IOPs are known, e.g., from an in-water instrument such as the ac9 (www.wetlabs.com). I finally studied the improvements in retrieved bottom classification if both bathymetry and water IOPs are known, which greatly constrains the inversion for bottom classification.

In addition to the constrained inversion work, I performed a detailed analysis of LUT bottom classification retrieval in the area of Horseshoe Reef itself, for which more detailed bottom classification information was available from underwater transects. A paper has been submitted on those results (Lesser and Mobley, submitted).

I also further streamlined the software and database search and spectrum matching algorithms, so as to speed up the processing time required for large images. The LUT database was also expanded with new sets of inherent optical properties. In particular, the new IOPs include particle backscatter fractions of 0.01, 0.02, 0.03, and 0.04. The previous database had only a 0.02 backscatter fraction for the clear-water IOPs used in the analysis of the imagery taken near Lee Stocking Island, Bahamas, as previously reported.

I also further studied the effects of atmospheric correction on LUT retrievals. That work (not discussed here) highlighted the need for improved atmospheric correction techniques, which are now being developed by my colleagues at the Florida Environmental Research Institute.

RESULTS

The LUT approach to retrieving IOPs, bottom reflectance, and bottom depth information from remote-sensing reflectances has performed well in its application to various PHILLS images (Mobley, et al., 2005). This year I analyzed additional imagery from the Lee Stocking Island (LSI), Bahamas, area, for which acoustic bathymetry and some IOP data were available. Figure 1 shows a PHILLS image taken near LSI; Fig. 2 is the corresponding acoustic bathymetry.

When doing an unconstrained retrieval on this image, the LUT bathymetry was on average 7% or 0.4 m too shallow; 66% of the pixels were within ±1 m of the correct (acoustic) depth, and 87% of the pixels were within ±25% of the correct depth. When the IOPs were constrained to be close to measured absorption and scattering values, the retrieved bathymetry was on average only 4% or 0.2 m too shallow; 64% of the retrieved depths are within ±1 m of the correct depth, and that 87% are within ± 25% of correct. This indicates that some improvement in bathymetry retrievals was obtained by constraining the IOPs. However, the improvement was not great, because the unconstrained LUT retrieval was already retrieving close to the correct IOPs. Thus constraining the IOPs did not make much difference in the retrieved bathymetry. It should be noted than some of the errors in bathymetry attributed to imperfect LUT retrievals are actually due to imperfect matching of the image pixel locations with the locations of the acoustic pings: it is difficult to get better than a few meters horizontal accuracy when doing the image warping and georectification.

Various LUT retrievals of bottom reflectance/type and water-column IOPs were made for unconstrained depths vs. constrained depths. Figures 3 and 4 show an example of the difference in the retrieved bottom classification. We see that when the depth is constrained, some areas retrieved as dense vegetation are reclassified as pure corals or less dense mixtures of mixtures of sediment, corals, sea grass, turf algae, and macrophytes. Some areas originally classified as sand with sparse vegetation are reclassified as bare sediment when the depth is constrained. Figure 5 shows the bottom classification when the IOPs are constrained to be similar to what was measured in this area. Figure 6 shows the results when both the depth and the IOPs are constrained. Again, the additional constraints result in some changes in bottom classification. Overall, though, there are no large changes in the bottom classification; dense vegetation never changes to bare sediment or vice versa, for example.

Thus constraining the depth causes some changes in the bottom retrieval, in terms of either the bottom reflectance (not shown here; see the related report on LIDAR bathymetry for examples of bottom reflectance retrievals) or classification. This is what is expected. The constrained retrievals are likely more accurate, but pixel-by-pixel bottom reflectances or classification are not available for validation of these retrievals. In either case, the retrieved bottom classification is plausible. The reason that the constrained retrievals are not greatly different from the unconstrained retrievals is that the unconstrained LUT depth and IOP retrievals are already close to correct. Constraining the depths or IOPs to be exactly correct thus has only a minor effect on the remaining parameters being retrieved. *This indicates that the LUT retrieval is not having any problems with non-uniqueness.* That is to say, LUT never finds an incorrect depth, incorrect bottom reflectance, and incorrect water IOPs that together give a remote-sensing reflectance that is close to the correct one. This is a reassuring check on LUT's ability to retrieve the correct environmental parameters in unconstrained retrievals, as will often be necessary in applications to denied-access areas.

Similar small changes are seen in the retrieved absorption, scattering, and backscatter spectra when the depth is constrained (results not shown here).

The results shown here will be presented in more detail at the Ocean Optics XVIII conference in October 2006. A paper on this work is being prepared for submission to either *Applied Optics* or *Optics Express*.

IMPACT/APPLICATION

The problem of extracting environmental information from remotely sensed ocean color spectra is fundamental to a wide range of Navy needs as well as basic science and ecosystem monitoring and management problems. Extraction of bathymetry and bottom classification is especially valuable for planning military operations in denied access areas. The fusion of hyperspectral imagery with LIDAR bathymetry (or other ancillary data as may be available about the imaged area) promises to improve the already impressive capabilities of hyperspectral imagery for extracting environmental information. This work thus adds to the existing suite of remote sensing analysis techniques for coastal waters.

TRANSITIONS

Various databases of water IOPs, bottom reflectances, and the corresponding R_{rs} spectra, along with the specialized Hydrolight code and spectrum-matching algorithms have been transitioned to Dr. Paul Bissett at the Florida Environmental Research Institute for processing his extensive collection of SAMPSON imagery now being acquired in coastal California waters, and for use in comparisons of LUT and LIDAR bathymetry.

RELATED PROJECTS

This work is being conducted in conjunction with Dr. Paul Bissett of FERI, who is separately funded for this collaboration. His ONR annual report should be consulted for the details of his contributions to the overall LUT development. This work also dovetailed nicely with separately funded work on the merger of hyperspectral imagery with LIDAR bathymetry. That work is described in a separate annual report. My own work is continuing with funding under a new contract number.

REFERENCES

Mobley, C. D., L. K. Sundman, C. O. Davis, T. V. Downes, R. A. Leathers, M. J. Montes, J. H. Bowles, W. P. Bissett, D. D. R. Kohler, R. P. Reid, E. M. Louchard, and A. Gleason, 2005. Interpretation of hyperspectral remote-sensing imagery via spectrum matching and look-up tables. *Applied Optics* 44(17), 3576-3592.

PUBLICATIONS

Lesser, M. P. and C. D. Mobley. Bathymetry, optical properties, and benthic classification of coral reefs using hyperspectral remote sensing imagery. *Coral Reefs* [Refereed, Submitted]

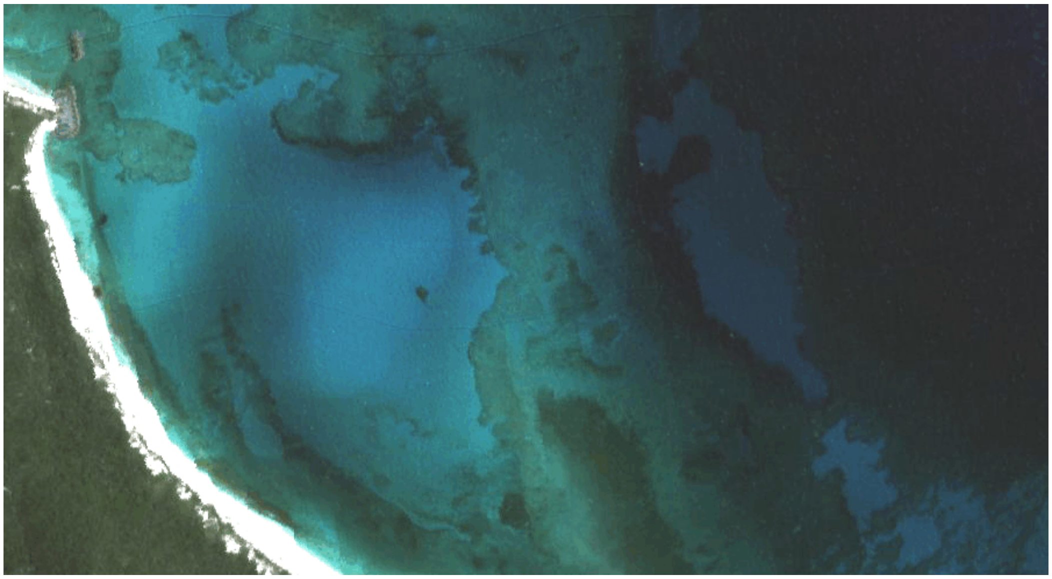

Fig. 1. An RGB image of the Horseshoe Reef area made from a PHILLS hyperspectral image taken May 20, 2000. The bottom includes areas of highly reflecting ooid sands, low reflecting, dense sea grass beds, and intermediate reflecting areas of mixed sediments, corals, sea grass, turf algae, and macrophytes.

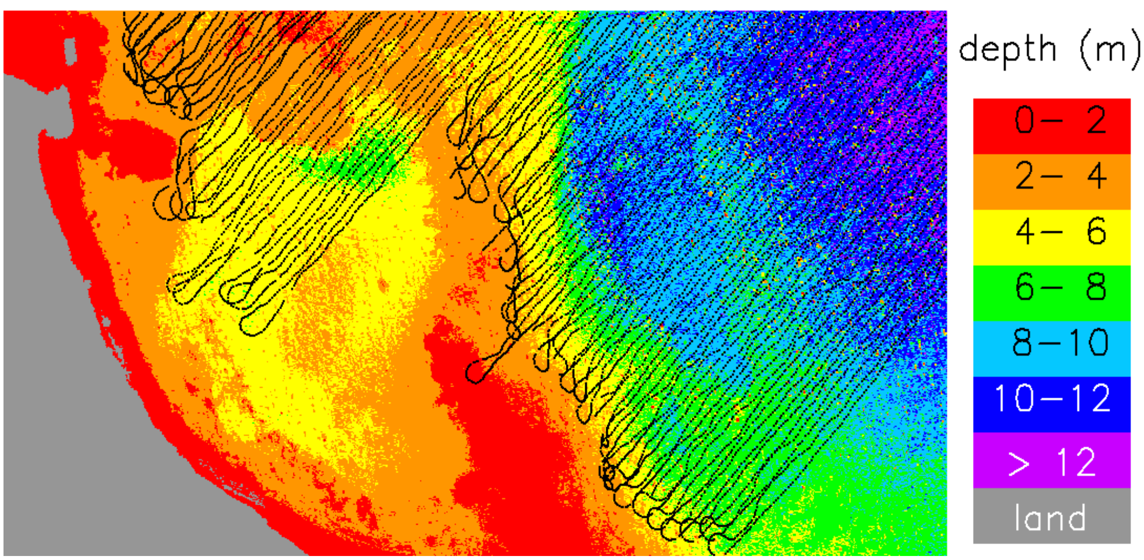

Fig. 2. Acoustic bathymetry coverage for the area corresponding to Fig. 1. The black dots show the locations of the acoustic pings. The depth at each pixel of the image of Fig. 3 is obtained by interpolation between the locations of the acoustic data, where available. Regions for which no acoustic data are available are omitted from further analysis. The color-coded depths are for the unconstrained LUT retrieval applied to the entire image.

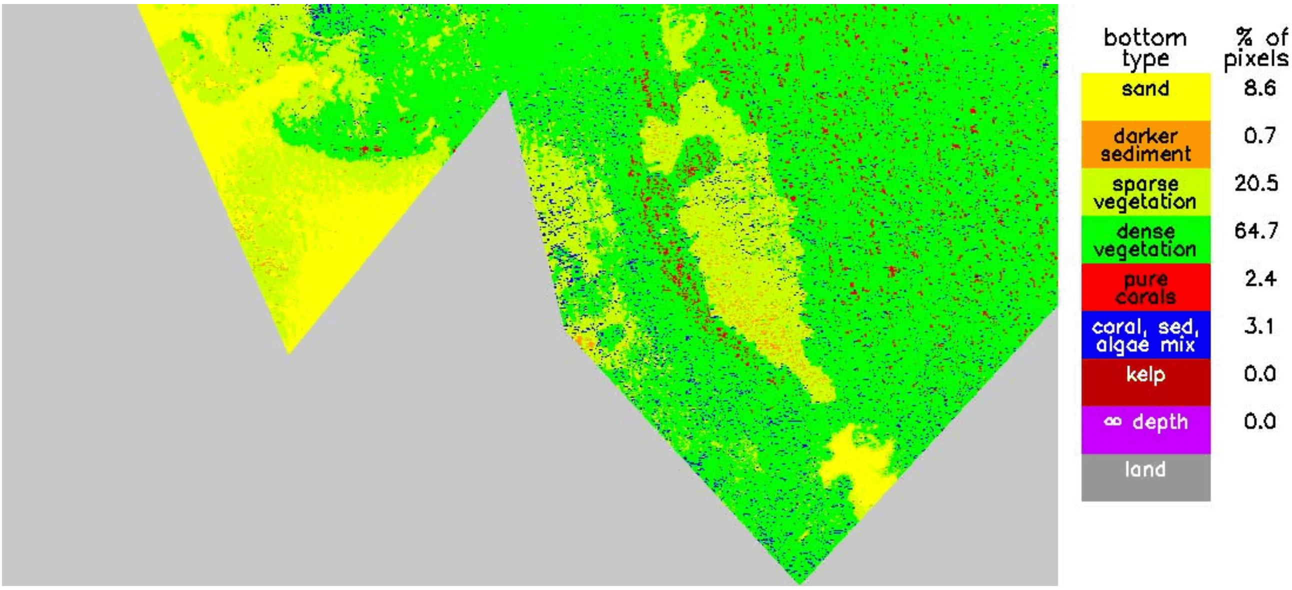

Fig. 3. Bottom classification for the unconstrained retrieval. The image region where no acoustic bathymetry is available is masked out. [The color coding identifies the bottom type, e.g., sand; sediment with sparse vegetation; dense vegetation; mixtures of sediment, corals, and algae; or infinitely deep water.]

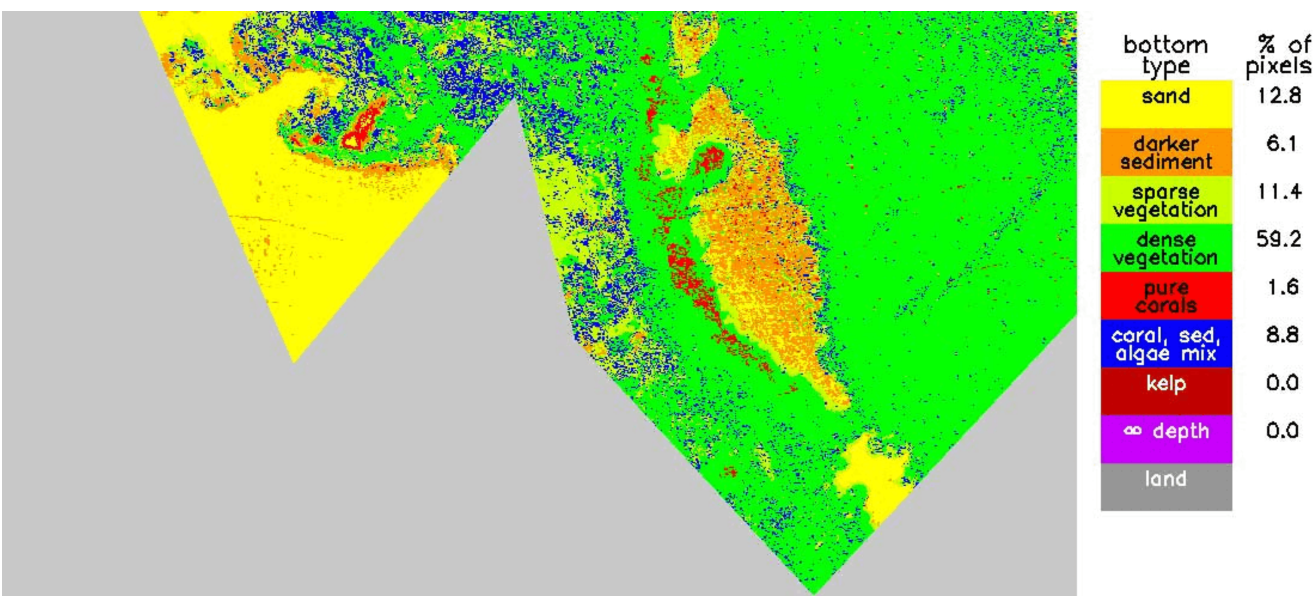

Fig. 4. Bottom classification for the depth-constrained retrieval. [color coded as in Fig. 3]

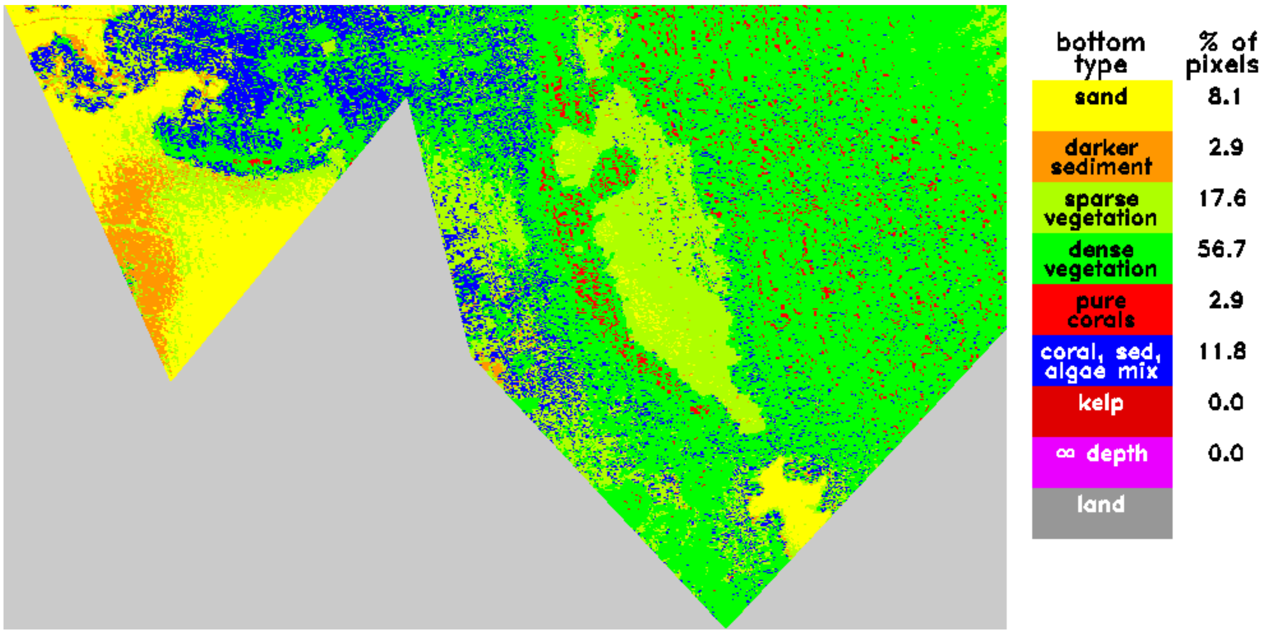

Fig. 5. Bottom classification for the IOP-constrained retrieval.

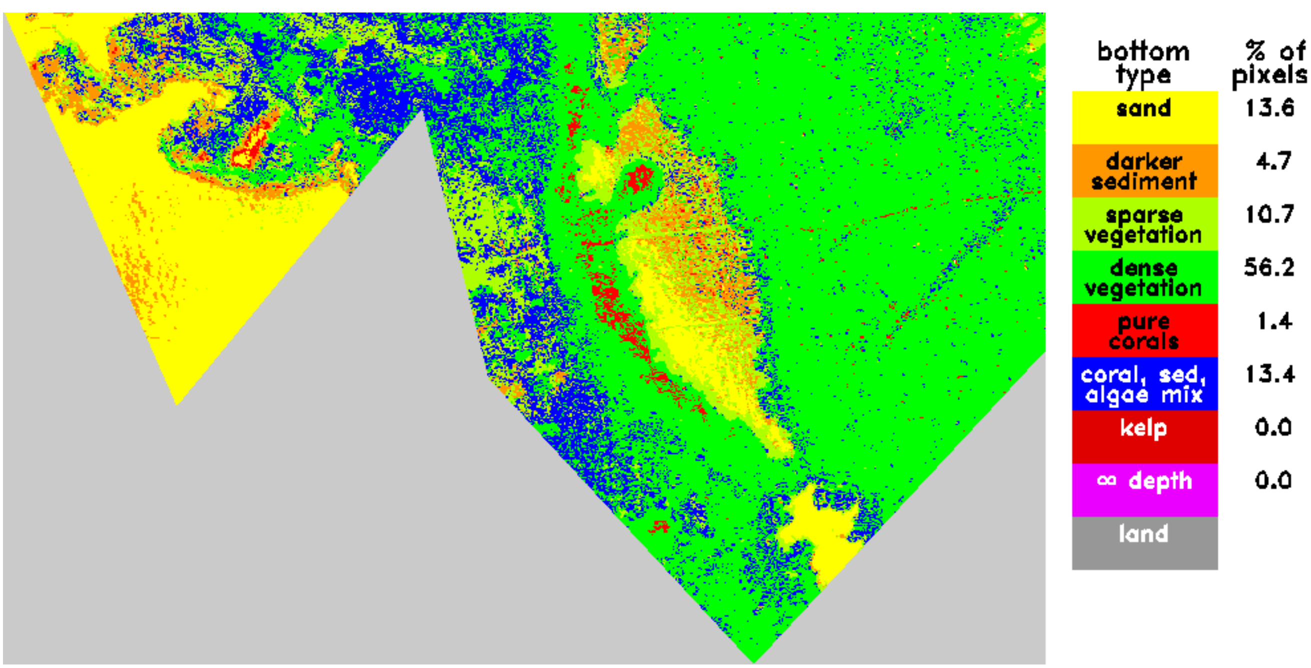

Fig. 6. Bottom classification for the depth- and IOP-constrained retrieval.